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Risk-constrained dynamic energy allocation for a wind power producer

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ABSTRACT

Participants in competitive electricity markets make their dynamic decisions under uncertainty. Choosing a time-inconsistent formulation can lead to an incorrect procedure for risk and, consequently, to a sequence of inappropriate decisions. In a market context with uncertainty in energy prices, the net income of a company is the result of selling their energy in the spot market and through bilateral physical contracts. The purpose of this paper is to describe a dynamic multistage stochastic programming framework for sequential decision making under uncertainty that allows wind power producers to maximize their profit for a given risk level on profit variability. In this context, Conditional Value at Risk (CVaR) has been chosen as a time-consistent and dynamic risk measure. An example is provided to illustrate the methodology proposed.

1. Introduction

1.1. Literature review

In deregulated electricity markets, the aim of a wind power producer (WPP) is to maximize their profit. The most common ways to sell energy are through the spot market and/or via bilateral contracting. High prices in the spot market are favorable for a WPP to increase sales in this market and decrease deliveries under bilateral contracts. On the other hand, a bilateral contract allows the producer to sell their energy production in the future at a fixed price, hedging against spot price volatility.

Most electricity markets in the world have at least a spot market trading floor as well as bilateral contracting. Researchers have developed models to consider both assuming risk hedging strategies by the producers [1,2]. A seminal paper [3] provided the theoretical framework to study the combined pool/bilateral dispatch. This framework is also valuable to negotiate bilateral contracts [4]. Other papers have studied how to procure energy for a retailer or a large consumer [5,6].

The majority of papers dealing with the interaction between spot prices and contracts have used static stochastic programming [7] but just a few have used dynamic programming [8]. Dynamic programming [9] offers the possibility to make the optimal decisions stage by stage, allowing for possible changes in demand, bids or other stochastic variables. This approach is used in the work presented here to provide a comprehensive framework for the energy allocation of a WPP that can sell in the spot market and is engaged in a bilateral contract.

One common option to sell energy is using firm commitments by renewable producers, as mentioned in [10]. In that paper, the authors show how firm energy commitments (FEC) are possible in Brazil. In the Brazilian regulatory framework, the yearly FEC is calculated by the maximum continuous energy delivery capability (in monthly periods). However, they require purchasing energy from the spot market in periods when the producer cannot fulfill the contract.

However, this work considers a flexible bilateral contract where a WPP determines the amount of electricity to be sold according to the contract at each time interval or stage, *t*, whereas the other contract party accepts the delivered electricity according to the WPP's decision.

The flexible contract proposed in this paper was already mentioned in [11]. In that paper there are two types of flexible contracts, the second one (type II) being the closest to ours. The seller of the

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contract optimizes the electricity to supply during each time period and the buyer has to accept this amount of electricity defined by the contract. A customer who has flexibility to consume electricity over a time horizon is likely to agree with this type of flexible contract.

One example of a flexible forward energy contract in Brazil is shown in [12]. In that paper, the authors use stochastic dynamic programming and explain that the main drive for a consumer to use this contract is low price. They say that in this type of contract, horizon, total volume, price and interval of discretization are previously established between the parts. In the contract, the maximum and minimum limits of the energy to be delivered in each interval of discretization are flexible.

1.2. Mathematical dynamic programming approach

The problem solved in this paper is of the stochastic dynamic type including risk aversion. There is a gap in power systems literature where dynamic problems with risk aversion are not appropriately addressed. Generally, power systems literature covers dynamic programming that ignores risk. Therefore, in conventional dynamic programming, a recursive function based on costs/profits and future expected costs/profits is proposed for each stage and solved recursively. Examples of this formulation are applied to the hydro planning problem [13], bid-based hydrothermal scheduling [14] or pricing of electricity flexible contracts [11]. However, if risk aversion is included in the decision process, a *time-consistent* risk measure is more convenient to use. Thus, if a time-consistent optimal policy is satisfied today, it will also be satisfied tomorrow with the same policy. The concept of dynamic time-consistent risk is relatively new. Ref. [15] proves that a time-consistent dynamic risk measure can be constructed in terms of a single-period risk measure, and it can also be constructed as a risk-coherent [16] risk measure. Few references have addressed dynamic problems with time-consistent risk measures applied to portfolio optimization [17] or hydro planning [18], but none has yet presented a time-consistent dynamic formulation for the WPP energy allocation problem. This research fills a void and goes beyond what has been done in the past regarding the energy allocation problem for a WPP.

In the dynamic programming formulation proposed, a *future utility function* (FUF) is built sequentially using a backward procedure. A time-consistent policy is generated with dynamic programming forward procedure using the generated FUF. Risk is taken into account by the WPP using a coherent dynamic CVaR metric and an example serves to illustrate our model.

1.3. Contributions and paper organization

The main contributions of this paper are fourfold:

1 To formulate a multi-stage stochastic dynamic problem for a WPP that allows us to make dynamic decisions for selling energy in both bilateral contracts and spot markets thought the contract time horizon.
2 To model a time-consistent and coherent dynamic risk measure to account for the risk under a dynamic decision setting.
3 To depict a future utility function definition to represent risk-averse dynamic preferences of a decision-maker consistent with the above dynamic risk setting.
4 To present an efficient formulation based on dynamic programming to solve the proposed model.

The paper is organized as follows. Section 2 presents the decision framework of a WPP. Section 3 shows a time-consistent dynamic risk measure definition that is applied to the proposed energy allocation problem in Section 4. In the latter section, a dynamic programming model is proposed first, and, second, a backward procedure is used to solve the problem using a discretized approach. Section 5 illustrates the methodology with a case study and Section 6 presents the conclusions obtained and directions for future research.

2. Decision framework

It is assumed that there is only one WPP owning several wind turbines, simplified to one unit for the sake of simplicity. The WPP is considered as a price-taker, i.e., (stochastic) spot prices are given data. The time horizon corresponds to the range of dates during which the WPP will make decisions. This time horizon has a duration determined by the type of contract signed between the WPP and the consumer. For simplicity, we also assume that there is only one contract available to the WPP, but many of them could be possible. The stages of the contract horizon are indexed as $t = 1, \ldots, T$. Each stage is divided into representative periods indexed as $h = 1, \ldots, H$.

Regarding the contract, a flexible bilateral contract is signed at stage $t = 0$. The flexibility is determined by the WPP which decides how much energy to sell and at each stage. That means that the contract is defined by:

- A price, λ^C (€/MWh), fixed for all stages and periods.
- A total energy volume, V (MWh), that can be sold or not throughout all the stages. If the energy sold through the contract at stage t is defined as $E_{th}^{WC}(\omega_t)$, the condition that must be met is $0 \le \sum_{t=1}^{T} \sum_h \sigma_h E_{th}^{WC}(\omega_t) \le V$.

A state variable, x_t, defines the amount of contract that has been already used up to stage t. This variable couples all stages in the sense that decisions taken today may affect the decisions taken tomorrow. Dynamic programming models are good for this multistage interaction. This allows a decision maker to take optimal decisions dynamically at each stage.

To model the uncertainty of the spot prices and the WPP generation, several price scenarios are generated with a correlation matrix. Thus, $\lambda_{th}^S(\omega_t)/E_{th}^W(\omega_t)$ represents the spot price/wind production at stage t, period h and scenario ω_t. The scenarios are assumed to be stage-wise independent.

Therefore, taking into account these requirements, the decisions that a WPP faces are illustrated in Fig. 1. The bilateral contract is signed at the beginning of the time horizon. Then, at the beginning of each stage, the WPP needs to decide the amount of energy to supply to the bilateral contract, E_t^C, during the next H hours with the same amount of energy for each hour. After the spot price and wind production realizations are known, the WPP decides the amount of energy to deliver to the spot market in each hour, $E_{th}^{WS}(\omega_t)$. A deviation penalty cost, μ^C, accounts for wind deviations if the delivered wind energy to the contract $E_{th}^{WC}(\omega_t)$ is less than the committed wind energy E_t^C. Observe that, in this paper, the contract price, λ^C, is given. If this contract price were lower than the price of a bilateral contract without risk, a contracting party (buyer) would accept the terms of such a contract, including risk, in order to obtain cheaper energy. The calculation of the optimal contract price that the buyer would be willing to sign for is out of the scope of this paper.

Each stage is divided into a finite number of hours. Typically a stage spans over a week and each week is divided into 168 h. For tractability reasons, the total number of hours is simplified and grouped into representative periods. Each one is weighted by a parameter, σ_h, representing the total number of hours of such a period. For example, a week can be divided into working days/holidays and peak/off-peak hours.